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Artificial Intelligence for U.S. Army Wastewater Treatment Plant Operation and Maintenance

by
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As the Army faces increasing reductions in budget and personnel for supporting functions such as operation and maintenance (O&M) of wastewater treatment plants (WWTPs), it is clear that reliance on automation will continue to grow. While computer systems will not replace operators, they will provide valuable assistance in optimizing the operator's time and effort.

An emerging technology with potential application to WWTP O&M is artificial intelligence (AI)/expert systems. These systems use knowledge bases developed by experts in a given field combined with a "reasoning" chain of logic to provide diagnostic and control functions. This study has investigated opportunities for exploiting AI and expert systems for increasing the performance and reducing the cost of Army WWTP O&M. In addition, a general orientation to the technology has been provided to assist Army personnel in making decisions about its applicability to their installations.

Findings suggest that AI/expert systems technology is not yet at an economically practical level for use in O&M of the Army WWTPs. However, as the technology becomes refined and produced at a lower cost, it should be reconsidered; this study has shown through a proof-of-concept exercise that AI/expert systems have potential value to the O&M process.

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FOREWORD

This investigation was performed for the U.S. Army Engineering and Housing Support Center (USAEHSC) under Project 4A162720A896, "Environmental Quality Technology"; Task B, "Environmental Design and Construction"; Work Unit 043, "Automated Army Water/Wastewater Treatment Process." The USAEHSC Technical Monitor was Thomas Wash, CEHSC-FU-S.

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ARTIFICIAL INTELLIGENCE FOR U.S. ARMY WASTEWATER TREATMENT PLANT OPERATION AND MAINTENANCE

1 INTRODUCTION

Background

Most wastewater treatment plant (WWTP) designers, operators, and managers believe that WWTPs should be designed, operated, and maintained in the simplest way possible. This principle clearly applies to U.S. Army-owned and -operated WWTPs, where poor efficiencies sometimes occur due to a shortage of operators and lack of training.

In recent years, it has been shown that computer systems can make WWTP operation and maintenance (O&M) easier and less costly. Many persons in the field now believe that the computer will be a necessary part of plant O&M in the very near future and that the computers will simplify, rather than complicate, the process.

Installations are required to comply with provisions of their National Pollutant Discharge Elimination System (NPDES) permits.[1] However, the General Accounting Office (GAO) reported in 1984 that a significant number of Department of Defense (DOD) plants were failing to operate within NPDES limitations.[2] In response to the various problems with Army WWTP operations, the Army Operators' Assistance Program (OAP) was implemented. Despite this action, there is still a need to improve WWTP O&M at military installations.

Artificial intelligence (AI) is a promising technology in terms of addressing the inevitable automation of WWTPs as well as the need for better O&M. The term "AI" has been used in computer science to indicate the study of ideas that enable computers to be "intelligent." Expert systems, a branch of AI, attempt to simulate human reasoning by chaining together the important facts in a given domain to arrive at conclusions logically. Recent research into AI/expert systems (ES) has seen much success in areas such as medical diagnosis, mineral prospecting, and chemical structure elucidation. A concerted effort is underway to exploit this new technology and extend it to applications for which human expertise is expensive or in short supply. The application of AI/ES may provide the Army with an innovative problem-solving tool to enhance and extend the limited personnel and budgetary resources for WWTP O&M. Therefore, the Army needs to evaluate the feasibility of applying AI/ES to WWTP O&M.

Objective

The twofold objective of this research is to (1) identify and evaluate potential opportunities for the Army to exploit recent advances in AI to improve the performance of its water and wastewater treatment facilities and (2) provide a general orientation to this emerging technology for Army installations that may be required to assess its value to their WWTP.

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[1] Army Regulation (AR) 200-1, *Environmental Protection and Enhancement* (Headquarters, Department of the Army, 1982).

[2] General Accounting Office, *DOD Can Make Further Progress in Controlling Pollution From Its Sewage Treatment Plants*, GAO/NSIAD-84-5 (February 1984).

Approach

Several alternative approaches were considered for surveying and analyzing the potential of using AI/expert systems in Army WWTP O&M. From these alternatives, three different approaches were adopted:

1. LISP Machine, Inc., Los Angeles, CA, was contracted to analyze the potential from an expert systems manufacturer's viewpoint.

2. A Stanford University research team developed a proof of concept by constructing and testing an expert system.

3. Dr. S. P. Shelton, University of New Mexico, looking toward the future, predicted how the expert system would evolve and assessed the cost/benefit aspect.

Information from these sources was analyzed for Army relevance.

Scope

This study is limited to an assessment of AI/ES that could potentially be applied to O&M at Army WWTPs. The proof-of-concept exercise performed by Stanford University focused only on an isolated part of the WWTP process and by no means is intended to be a prototype system for the Army; the point of the exercise was only to show feasibility of using AI technology in WWTP O&M.

Mode of Technology Transfer

It is recommended that information from this study be incorporated into Technical Manual (TM) 5-665, *Operation and Maintenance of Domestic and Industrial Wastewater Systems* (January 1982) and TM 5-814-3, *Domestic Wastewater Treatment* (November 1978).

2 ARMY WASTEWATER TREATMENT PLANTS (WWTP) AND ARTIFICIAL INTELLIGENCE (AI)

Army WWTP

Results of a 1980 in-house Department of the Army (DA) WWTP survey indicated that the major problem with O&M at Army WWTPs was a shortage of operators and lack of training. In 1984, GAO found that most randomly sampled DOD WWTPs had not consistently met the effluent quality limitations imposed by their NPDES permits. This situation was due to inadequate staffing, a lack of specific guidance on adequate operation, maintenance, and compliance, and a poor maintenance program. In response to various problems with the Army WWTP operation, DA initiated the OAP through the former Facilities Engineering Support Agency (FESA) and WWTP performance improved. However, there is a need for additional improvements.

One area still needing attention is the effluent quality mandated by NPDES permits. Typical secondary treatment plant effluent limitations that WWTPs should meet are:

- BOD and suspended solids (SS): 30 mg/L for a 30-day average and 45 mg/L for a 7-day average

- Percentage efficiency: more than an 85 percent removal of influent BOD and SS for a 30-day average.

More stringent mandates or other limitations such as pH, fecal coliform, settleable solids, residual chlorine, total Kjeldahl nitrogen (TKN), ammonia, and phosphorus levels may be required, depending on the receiving water quality. Some WWTPs are still not meeting these requirements.

The major areas of concern that could potentially be addressed through AI application to WWTP O&M are:

- Operator training

- Proper operation and control techniques to meet NPDES permit limitations

- Efficient operation to minimize the operating costs (i.e., manpower, energy, and chemicals)

- Plant operation and laboratory records management

- Reporting as required by in-house management and the regulatory agencies

- Preventive and scheduled maintenance programs

- Process control

- Corrective maintenance and troubleshooting

- Planning, scheduling, and budgeting.

Automation and Computerization of WWTPs

Automation is not a new subject for WWTP designers and operators. Proceedings of an International Association on Water Pollution Research and Control workshop[3] and an American Water Works Association (AWWA) management resource book[4] summarize the current status of automation and instrumentation for WWTPs and water plants. In these references, many workers reported that computerization of WWTPs and water plants had saved operating costs through increased performance efficiency and optimal use of energy and chemicals. Areas in which automation and computerization proved to be efficient and reliable include: WWTP process control, information management, monitoring, water plant unit process operation, pumping station operation, wastewater disinfection, plant energy optimization, water distribution optimization, and maintenance management. No water plants or WWTPs are currently operated by an expert system, but some workers use an expert system-based technique.[5] In 1980, Kelley[6] stated that the computer could not be justified for water plants smaller than 20 mgd. In 1986, Poon et al., concluded that the adoption of a microcomputer-based O&M system would be beneficial for new or larger (4-mgd or more) water plants and WWTPs.[7]

Instrumentation is an important part of WWTP automation and computerization because adequate monitoring and process control are not possible without it. One of the most important features of instrumentation is the sensor; sensing devices are even more critical when automation or AI/ES is implemented. Some sensors are readily available and reliable, while others are not. Table 1 summarizes the current state of the art in sensors.

Artificial Intelligence and Expert Systems

AI-based expert systems are computer programs in which logical reasoning is supplemented by theoretical knowledge, judgment, and rules of thumb. Expert systems solve problems that generally fall into one of the following categories: interpretation, prediction, diagnosis, debugging, design, planning, monitoring, repair, instruction and control.

History

In the late 1960s, early AI researchers believed that a few laws of reasoning coupled with powerful computers would produce expert, superhuman performance. As experience accrued, research began to focus on narrowly defined applications. From the

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[3]R. Drake (Ed.), *Instrumentation and Control of Water and Wastewater Treatment and Transport Systems* (Pergamon, 1985).

[4]American Water Works Association (AWWA), *Computer-Based Automation in Water Systems* (1980).

[5]D. Johnston, "Diagnosis of Wastewater Treatment Processes," *Proceedings, Specialty Conference on Computer Applications and Water Resources* (American Society of Chemical Engineers [ASCE], June 1985).

[6]AWWA, p 12.

[7]C. P. C. Poon, et al., *Evaluation of Microcomputer-Based Operation and Maintenance Management Systems for Army Water/Wastewater Treatment Plant Operation*, Technical Report N-8618/ADA171992 (U.S. Army Construction Engineering Research Laboratory [USA-CERL], July 1986).

Table 1

Important Variables and Availability of Sensing Equipment*

Area of Application	Variable	Equipment Availability**
Water quality monitoring	Chlorine residual	2
	Iron	3
	Manganese	3
	Aluminum	3
	Heavy metals (Cu, Cd, Hg, etc.)	3
	Turbidity	1
	Color	2
	Organic matter	2
	(UV absorption)	2
	Taste	-
	Odor	-
	Toxic organics	3
	Treatability	3
	Ammonia	2
	Nitrate ion	2
Sewerage systems	Liquid flow	3
	Liquid level	2
	Liquid pressure	2
	Treatability	3
	Toxicity	3
Gases	Flow/pressure	1
	Dissolved oxygen	2
	Hydrogen sulfide	2
	Methane	2
	Carbon monoxide	2
	Carbon dioxide	2
Sewage treatment	Liquid flow	2
	Liquid level	2
	Sludge blanket level	2
	Sewage (suspended solids)	3
	Mixed liquor (suspended solids)	2
	Returned sludge (suspended solids)	2
	Surplus sludge (suspended solids)	2
	Dissolved oxygen	1
	Treatability/toxicity	3
	Oxygen	1
	Flow (sludge gases)	2
	Pressure (sludge gases)	2
	Calorific value (sludge gases)	2
	Methane (sludge gases)	2
	Carbon monoxide (sludge gases)	2
	Carbon dioxide (sludge gases)	2
	Oxygen (sludge gases)	2
	BOD	3
	pH	1
	Fecal coliform	3
	Ammonia	2

Table 1 (Cont'd)

Area of Application	Variable	Equipment Availability**
River management	Flow	1 & 2
	Level	1 & 2
	Temperature	1
	Dissolved oxygen	1
	Ammonia	2
	Nitrate ion	2
	Chloride ion	2
	Conductivity	1
	Heavy metals	3
	Trace organics	3
	Biologically based sensors	3

*Source: R. Drake (Ed.), *Instrumentation and Control of Water and Wastewater Treatment and Transport Systems* (Pergamon, 1985). Used with permission.

**Availability code: (1) readily available; (2) sensors available, not necessarily in a form suitable for the application--therefore, the system requires development; (3) in experimental or prototype stage.

mid-1970s through the early 1980s, work in the expert systems field achieved much success, examples of which include:[5]

- PROSPECTOR has discovered a molybdenum deposit for which the ultimate value will probably exceed $1 billion.

- R1 configures customer requests for VAX computer systems at Digital Equipment Corporation, despite the fact that even the resident experts thought it could not be done.

- DENDRAL, which years ago demonstrated superhuman performance, supports hundreds of international users daily in chemical structure elucidation.

- CADUCEUS embodies substantial knowledge of internal medicine and has correctly diagnosed complex test cases that had stymied human experts.

- PUFF has integrated knowledge of pulmonary function disease with a previously developed domain-independent expert system for diagnostic consultations and now provides expert analyses at a California medical center.

[5] F. Hayes-Roth, D. Waterman, and D. Lenat, "An Overview of Expert Systems," *Building Expert Systems* (Addison-Wesley, 1983).

Basic Concepts of an Expert System

The architecture of an expert system contains two fundamental components: the knowledge base and the inference engine. Figure 1 shows the components of a complete expert system.

The knowledge base--the foundation of an expert system--is where the information required to emulate human expertise is stored. It differs from a database because the nature of human knowledge about a domain of expertise is not purely factual. Real-world knowledge is a much more subtle collection of rules, procedures, and relationships, as well as simpler facts or assertions, which must be represented and structured in such a way that it can be conveniently stored in computer memory and accessed by the inference engine.

A key step in AI research was the insight that a vital part of this knowledge is embodied in "heuristics"--that is, practical working rules rather than theoretical models learned from experience and, often to some extent, beyond conscious recall. These heuristics guide the human expert to select correct solutions quickly and efficiently among a multitude of alternatives.

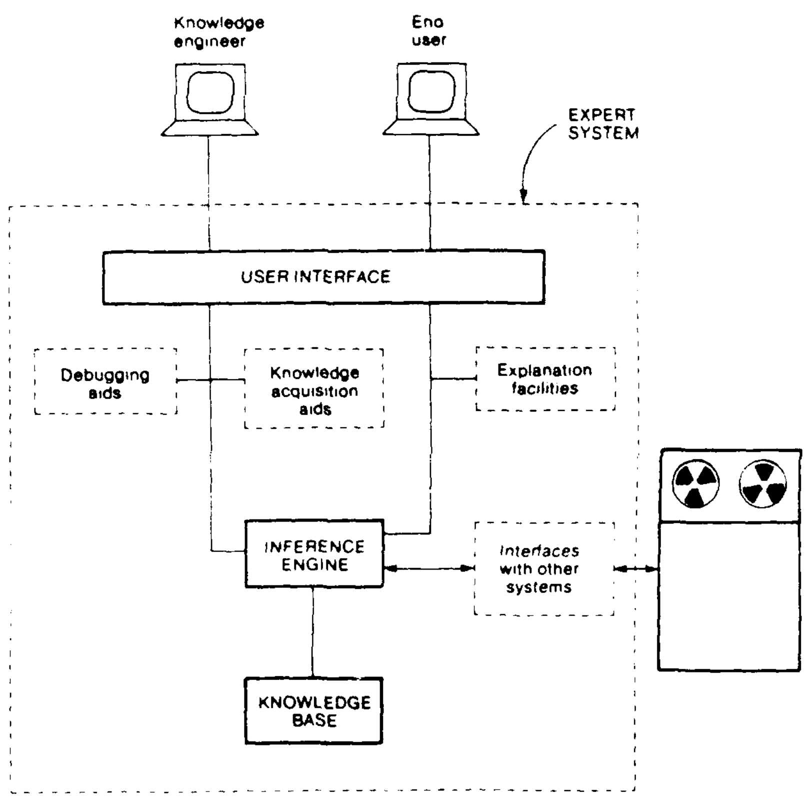

Figure 1. Architecture of an expert system.

Identifying and representing the heuristics are major parts of developing a knowledge base; this task is one of the main factors determining if the development of an expert system is easy, difficult, or infeasible. Key considerations are that the systems must be restricted to a limited, clearly defined knowledge domain, and that the heuristic knowledge must be available in some form--either from a human expert or documentation.

The function of the second major expert system component, the inference engine, is to operate on the knowledge base and apply the laws of logical inference to make further deductions about the situation it describes. An inference engine, separated from the knowledge base, represents the abstract rules of logic that ideally are independent of any specific knowledge domain. In practice, however, knowledge bases frequently contain procedural information that guides the inference engine through the knowledge base, thus saving research time. Such information is sometimes called "metaknowledge," or knowledge about the knowledge itself.

Compare this structure with a conventional algorithmic program working against a database. The program is a fixed representation of actions that should be taken in its domain, depending on alternative facts provided. Although the facts in the database may vary, the domain knowledge in the program cannot be changed without reprogramming. In an expert system, new rules and procedures can be added to the knowledge base as required, and each updating of the knowledge base can create the equivalent of a new algorithmic program.

Besides the knowledge base and inference engine, the other essential elements in an expert structure are the interfaces that link these two components to the outside world, generally to a human user at present, but increasingly in the future to other computer programs and conventional databases. A frequent requirement, sometimes regarded as an essential feature of the expert systems, is an explanation facility that can trace the line of reasoning a system has used to reach a conclusion and present it to the user in an understandable form.

The expert system's architecture also dictates the nature of the tasks to be carried out by the users and the talents they need. The architecture is successful because it places the emphasis of new systems development on the acquisition and organization of domain knowledge. This condition, in turn, has created the need for "knowledge engineers" who have the ability, training, and experience to elicit knowledge from domain experts and structure it appropriately in the knowledge base, designing the whole system so that it can arrive at required solutions quickly and effectively. Thus, the whole technology can be seen as a means of increasing the leverage that skilled persons can apply to solve problems using computer-based solutions.

Example of a Commercial Expert System

As an example of the type of expert system currently available on the market, the PICON system is described here based on literature from the manufacturer. Los Angeles-based LISP Machine, Inc. (LMI), is a supplier for the PICON system, an integrated hardware/software environment built for industrial process management using AI technology. The hardware/software implementation of this system requires:

- An intelligent computer interface to acquire data from sensors and actuators of the physical process as required for making decisions.

- A technique to process incoming data so that it is directly usable for decision making.

- A way to enter the expert's knowledge into the computer's knowledge base by the domain expert with no AI background.

- A way to access expert advice and explanations by the process or factory operator.

- An inference engine capable of processing large, complex problems, applying expert knowledge to real-time data and responding in a matter of seconds.

System Features

According to LMI, for real-time response to the thousands of dynamic data points of a large real-time system, PICON is designed with unique features, including: online data collection; scanning; focus; scheduling; long-term strategy; background maintenance; and simulation. These capabilities are summarized below.

Online Data Collection. PICON interfaces directly to the process control data via its RTIME interface module. It selectively accesses the data needed for inference and decision-making. All data is then stamped and carries a user-selected currency interval that defines the life of data.

Scanning. PICON can scan certain conditions at regular intervals to look for incipient upsets, problems, or significant events. The user can specify a scan rate for the rules that control this activity.

Focus. Some sensors need to be read, and some rules tested, only when a certain situation has occurred. These secondary rule-frames are activated by the primary alerting rules, causing PICON to focus on parts of the process related to the actual or developing problem detected by the primary rules.

Scheduling. At the heart of the PICON inference engine is the scheduler. Online applications require that data be obtained from other control or automation systems, but it may not arrive in time for a particular inference. PICON's scheduler is responsible for: (1) interrupting and resuming inferences and actions that are not complete due to a lack of data; (2) taking alternative actions when an inference does not complete in a reasonable amount of time; and (3) keeping many activities going without ambiguity. It can schedule any number of activities, such as testing a rule, to occur on a regular, cyclic basis. It can also schedule any activity to occur at some specific time in the future, whether in 3 seconds or 3 weeks.

Long-Term Strategy. An expert system that could respond only to a current situation would be of limited utility in most applications. PICON is designed to deal effectively with the rates of change, and any abnormal trends in the process.

Background Maintenance. Because of PICON's large LMI Lambda/Plus LISP Machine and unique scheduling facility, many thousands of activities can be scheduled in the background without interfering with the system's ability to focus on the current situation. These activities may include routine inspection of sensors or other pieces of equipment to detect failures or marginal performance.

Simulation. PICON is supplied with a dynamic simulator that has the same user interface as the knowledge-base editor. The simulator is a distinct module that supplies sensor values to the inference engine as if they were obtained from a real plant. The user can select the source, i.e., simulation or real process, from which PICON captures its data. The simulation can be developed and tested incrementally as the knowledge base is being built, making it an ideal tool for testing the knowledge base and checking PICON's response to both normal and abnormal conditions. The simulator is also very useful for training operators, as it can be used to expose them to situations seldom encountered.

Interface Program

PICON interfaces with a real-time data source such as a process control system for real-time data acquisition via the RTIME interface. RTIME consists of three functional submodules:

1. LISP Communicator Module: provides efficient, effective communication between the programs that run in the LISP and RTIME processors. All LISP communication, including shared memory used for storage and access to data in engineering units, is invisible to the user. The user interface is a user-friendly, icon-based screen operated with a mouse.

2. Execution Module: where RTIME performs all of the preprocessing functions called by the user as a part of the node descriptor table. A "node" is a designated data source in a process or a plant network. RTIME is enriched with a library of commonly used algorithms. Specialized algorithms can be added to this library to suit a problem domain.

3. I/O Driver: the element of RTIME that inputs and outputs data on the interconnect device chosen to communicate with the external system. Standard communications are via Multibus, high-speed RS232, Ethernet, and other Multibus-compatible interfaces. Since PICON is applicable to a variety of data-acquisition systems with differing protocols, it is often necessary to customize this part of RTIME to a specific network.

PICON can send expert advice to the operator and/or the process to change a process variable (e.g., controller setpoint in a closed-loop situation). The system is designed to be compatible with existing color displays commonly offered by process control vendors to display PICON decisions on these terminals.

The explanation facility in PICON allows a user to ask the system to explain its decision process. This information is presented to the user graphically in the form of a decision tree, which the system creates dynamically for every situation. LMI also claims that modifications and additions can be made to the knowledge base without stopping PICON.

Drawbacks With Direct Application

Although PICON is considered to be state-of-the-art in the AI industry, it is apparent that, at this time, LMI has little experience with wastewater treatment and the nuances associated with biological kinetics and related complexities. Oversights of this type are common among those who have had extensive experience in developing operational control systems for the chemical industry and seek to transfer that expertise to biological wastewater treatment. However, it has often been found that the heterogeneity of biological systems is such that the required complexity of control far exceeds the

expectations of those who normally deal with pure chemical systems. This criticism should not be inferred as an effort to denigrate information from LMI. Certainly the LMI approach would offer a substantial foundation from which an AI system could be developed for application to Army wastewater treatment process control and management; however, it should be recognized that the off-the-shelf transference of current LMI products is not the panacea that one might perceive from reading the manufacturer's literature.

3 FEASIBILITY OF AI APPLICATION TO ARMY WWTP

Application of AI has potential as an innovative problem-solving tool that could optimize the Army's limited resources for WWTP O&M. However, it must be understood that the AI approach for improving O&M will not replace human activity, but will provide a higher level of human-machine interface. AI application to O&M at Army WWTPs could possibly evolve in four different phases as summarized below:

1. The first phase would produce technology analogous to an unabridged dictionary on WWTP O&M. The information would apply to all WWTPs and, therefore, contain far more data than is needed for a particular plant operation. The operator would query the knowledge base through a sequence of keywords or topics and receive, in return, information regarding characteristics of the unit operation that is experiencing difficulty. There would be no feedforward or feedback chaining between a computer and a plant in operation. Therefore, the operator would have to rely on self-generated plant operation and laboratory data relative to plant performance.

2. The second phase in this evolution would be to tailor the first-phase expert system on a plant-by-plant basis. In this way, a more succinct knowledge base could be developed and the complexity of searching efforts for a specific problem will be lowered. As with the first-phase expert system, this system would have no direct interface with the operations and would simply act as an inquiry system using operator-supplied data.

3. The third phase would produce a recognition system. The term "recognition" is used in reference to an AI system's recognizing a problem and defining the problem variables for future action. In WWTP process control, the role of recognition is shared between the instrumentation for sensing and process control, and the knowledge base in the computer. The direct linkage between instrumentation and the computer would permit forward/backward chaining, thereby providing the potential for recognition of problems as they occur. The intelligent computer would suggest what needs to be done to correct the problem and the operator would implement this suggestion. In this phase, the operator action would yield new input data to the system, which would then generate a new frame. In this real-time environment, the system will "learn" as a function of operator action and the resulting cause-and-effect relationships.

4. The final phase would generate real-time control, which would free the operator from routine WWTP O&M and rely primarily on the AI system. In this scenario, the computer would operate and maintain the plant by adjusting flow and recycle rates; turning on and off valves, pumps, and blowers; adjusting chemical dosage; lubricating and replacing parts; and whatever else is needed for O&M. Operator intervention would be required only when a null set occurs in the AI system, in which case the system notifies the operator that an experience has occurred for which information is not available. Development of this type of system would require all information from the preceding three phases plus computer implementation of the action suggested in the first stage of AI development. Under this system, a computer-initiated action would yield a new frame. Thus, the chaining would appear in terms of "cause, action, effect, cause, action, effect, etc." If backward chaining were also used, the reverse of the above scenario could be incorporated in parallel, as well--specifically, "effect, action, and cause; effect, action, and cause; etc." The framing technique proposed would produce child frames as a function of new data while discarding parent frames. As time passes, efficiency and sophistication of the AI operating system would be brought into sharper focus for the specific treatment facility to which the AI system has been applied in a generalized

form. Therefore, the AI system, once implemented in generic form would evolve to become unique to the specific facility as a function of the learning process incorporated into the AI procedure.

Although AI technology has seen impressive progress in recent years, the successes described in the literature tend to exaggerate. At present, the above evolution scenario sounds exciting, but in the real world, the technology and resource limitations, for example, make the last phase infeasible from an economic perspective. However, AI applications can be expected to continue growing rapidly in coming years.

In this study, as the first step toward AI application to Army WWTPs, a proof of concept approach is proposed to explore the possibility of, and identify problems associated with, this application. The expert system in this study was constructed and tested by a Stanford University research team. The following portion of this chapter is adopted from the Stanford team report.[9]

Knowledge Acquisition

An early stage in creating an expert system involves formalizing the problem-solving approach of one or more individuals. This process often is called "knowledge acquisition." According to Buchanan and Shortliffe,[10] knowledge acquisition is "the transfer and transformation of problem-solving expertise from some knowledge source to a program." A clear understanding of the knowledge acquisition process will help the expert systems developer focus on the integral components of the planned system. To define the knowledge acquisition process for this study, each of the following phrases is defined: "knowledge source," "problem-solving expertise," "transfer," and "transformation." Some concepts not included explicitly in this definition (but discussed below) concern the roles of the system builder, otherwise known as the knowledge engineer, and the system user in knowledge acquisition.

Problem-Solving Expertise

The problem-solving ability within a specific domain is what separates experts from novices. This ability, usually gained after prolonged experience with a specific class of problems, allows the expert to solve problems quickly and efficiently. Experts rely on facts, combined with procedural and heuristic problem-solving methods. Facts include statements such as, "the dissolved oxygen is 4.5 mg/L," and "the primary clarifier was built in 1978." Procedures include methods for activities such as collecting and analyzing laboratory samples, cleaning and lubricating a pump, and calculating the sludge removal rate. Some procedures take the form of algorithms--computational methods guaranteed to provide a correct (or "optimal") solution in a finite period of time, or to conclude that there is no possible solution. Other problem-solving methods are heuristic, often consisting of rules of thumb that include symbolic information such as: "if the primary clarifier effluent solids are too high and gas bubbles are rising to the surface, then the sludge has

[9]L. Ortolano and C. Perman, *Development of a Conceptual Plan for the Exploitation of Artificial Intelligence in the Diagnosis of Operational Problems at Army Wastewater Treatment Facilities*, Draft Report, DACA 88-86-0247 and DACA 88-86-0008 (Department of Civil Engineering, Stanford University, May 1987).

[10]B. Buchanan and E. Shortliffe (Eds.), *Rule-Based Expert Systems: The MYCIN Experiments of the Stanford Heuristic Programming Project* (Addison-Wesley, 1984).

become anaerobic and is overflowing the weirs." An interesting characteristic of heuristics is that, although they often solve problems, they are not guaranteed to provide optimal solutions. Much of the knowledge acquisition process is concerned with defining the heuristic problem-solving techniques used by experts.

Knowledge Sources

In building an expert system, knowledge is gathered from both public and private sources. Public sources include documents prepared by the Environmental Protection Agency (EPA) and the Water Pollution Control Federation (WPCF). Generally, the public knowledge source consists of all material available as public domain, including material in textbooks, regulations, and videotapes. Public knowledge is available to more than one individual and is subject to peer review.

Expert systems rely heavily on private knowledge--especially the individual experts in a field. Often, private knowledge has not been formally documented and, in some cases, individuals may never have discussed their problem-solving approaches with anyone or had them reviewed by other individuals. Although public knowledge is used to the extent possible, knowledge acquisition focuses mainly on the knowledge held privately by individuals.

Knowledge Transfer and Transformation

Transferring knowledge means extracting and recording it from both public and private sources. Extracting knowledge from public sources is a well known exercise. The challenge of knowledge transfer lies with extracting personal knowledge from individuals. The knowledge acquisition process must be structured such that the individual's knowledge is captured and articulated in a way that allows it to be recorded. Three conditions have caused the knowledge acquisition process to be called "ad hoc" and characterized as being fraught with difficulties and frustrations: the nature of private knowledge, including its heuristic aspects; the dependence on an expert's ability to communicate; and the importance of the knowledge engineer's ability to listen.

In the context of expert systems, the transfer of private knowledge involves two-way communication between the expert and another individual, called the "knowledge engineer." Sometimes experts can record their problem-solving expertise independently. An advantage of using a knowledge engineer, however, is that he or she can contribute an objective view of which knowledge is pertinent to the planned expert system and often can direct experts in unraveling methods that they may never have formally identified. The assistance provided by the knowledge engineer can save the expert time during system development.

Methods used or formalized in communicating knowledge from the expert include: discussions and interviews organized by a knowledge engineer, surveys, interactive computer programs, the expert's critique of implemented prototype expert systems, and reactions of one expert to points raised by another.[11]

The transformation of knowledge, also the knowledge engineer's responsibility, consists of changing the recorded knowledge into formal expressions suitable for an expert system's programming environment. AI specialists have developed many schemes for

[11]P. Sell, *Expert Systems: A Practical Introduction* (Halsted Press, John Wiley and Sons, 1985); F. Hayes-Roth, D. Waterman, and D. Lenat.

representing expertise in a programmable format, including predicate calculus, n-tuples, semantic nets, frames, inference methods, and production rules.[12] In cases for which specific software and hardware have been chosen, the knowledge engineer must adapt the recorded problem-solving expertise to the syntax and representation schemes available. One of the indirect accomplishments of the transformation process is clarification of the expert's heuristic reasoning process. Since an explanation of the reasoning process is included as part of an expert system, clarity of expression is a requirement in formalizing heuristic knowledge.

One method of creating production rules based on case study examples, called "induction," is implemented with the help of specialized software.[13] Induction is based on a set of case studies, provided by the expert, which consists of different types of problem-solving decisions (e.g., a "training set") and a set of relevant factors called "attributes" that influence decision. The induction algorithm uses the training set to induce general principles, thereby formulating a generalized decision process and enabling the prediction of decisions for problem examples not included in the training set. The induction method is most useful in the later stages of the knowledge acquisition process when the expert, sometimes with the help of a knowledge engineer, has compiled a large number of case studies.

The Knowledge Engineer and the System User

The knowledge engineer is responsible for facilitating the knowledge transfer, transcribing and formalizing the knowledge and, in some cases, implementing the expert system. Sometimes several knowledge engineers work as a team; in other situations, a single person carries out all knowledge acquisition tasks. When the knowledge acquisition process is based on interviews and discussions, the knowledge engineer takes an active role in the knowledge transfer. In this context, the knowledge engineer, either consciously or unconsciously, can filter the knowledge by selecting or altering information as it is recorded and formalized. It is crucial that the experts have an opportunity to review and refine the recorded material and its implemented version. In some circumstances, the knowledge engineer can also function as a knowledge source. For example, the knowledge engineer might have some expertise in the problem-solving area. Although the knowledge engineer's abilities may be less refined than the expert's, they may be sufficient to contribute knowledge to the expert system.

The users are the individuals who ultimately employ the production version of the expert system. If they dislike the system, feel uncomfortable with it, or fail to find it useful or worth the time it takes to learn, they will not use it. Consequently, identifying the user's needs is essential to the design and implementation of the expert system. By consulting the users at the start of knowledge acquisition, they become a knowledge source--not so much for problem-solving expertise, but for giving feedback on the appropriateness of the input and output and on the effectiveness of the explanation facility. Knowledge acquired from consulting with the user applies specifically to the expert system's ability to communicate with the user (i.e., interface design) and the content of the explanation facility. If the explanation facility does not fulfill the user's needs, then the expert system is not attaining one of the defining characteristics of such a system: clarifying the program function to the user.

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[12] N. Nilsson, *Principles of Artificial Intelligence* (Tioga Publishing Co., Palo Alto, CA, 1980); E. Rich, *Artificial Intelligence* (McGraw-Hill, 1983).

[13] A. Hart, "The Role of Induction in Knowledge Elicitation," *Expert Systems*, Vol 2, No. 1 (1985), pp 24-28.

Knowledge Acquisition Methods for Developing a Prototype

The Stanford University research team conducted a knowledge acquisition exercise as a part of this study. The exercise serves to demonstrate the feasibility of using AI/ expert systems in developing a prototype for WWTP O&M at Army installations. The researchers served as the knowledge engineers, with five experts and one user (a novice operator) selected to complete the team. The knowledge was used to create a proof-of-concept system called "Sludgecadet," which was developed and tested for an isolated part of the O&M process. The exercise and the Sludgecadet system are summarized below.

Selecting the Expert

What are the appropriate criteria for selecting an expert? As a practical matter, the expert is someone who is regarded by those interested in solving the problem as having an outstanding record of accomplishment.

For this study, an "expert" was defined as a person who meets the following criteria:

- Diagnosis and repair expertise
- Interest in participating
- Familiarity with Army facilities
- Ability to communicate effectively
- Computer literacy
- Compatibility with the knowledge engineer
- Time availability.

Based on these criteria, five experts were selected--three from ES2 Engineers, Berkley, CA, and two operations foremen from the Fort Lewis, WA, WWTP. The ES2 Engineers experts provided general expertise in diagnosing problems and recommending actions while the Fort Lewis foremen supplied site-specific knowledge for building the expert system.

Transferring Knowledge From Experts

The team planned to transfer knowledge from the experts to the computer program in cycles, with each cycle consisting of the following steps: interview, transformation, implementation, demonstration, review, and refinement. Interviews were used to gather new knowledge which was then transformed into programmable form. Implementation of the knowledge as a component of the prototype expert system was then demonstrated to the experts and their review comments were used to refine it. The experts were involved at the interview, demonstration, review, and refinement stages, whereas the knowledge engineers participated in all stages. Each cycle began by collecting the more general expertise from the ES2 experts and ended by having the Fort Lewis foremen add site-specific expertise.

During each interview, the knowledge engineers and an expert developed a test case. The various elements of the expert's problem-solving techniques were revealed by

examining how the expert discovered a problem symptom, how the cause of the various symptoms were diagnosed, and how a particular remedial action was recommended. The rules articulated in the context of the test cases came from the expert's own experiences. Other rules were deduced from an expert's reactions to case histories developed by other experts and reported in the literature. After these interviews, the knowledge engineers formalized and added each test case to the developing expert system.

The next step in transferring knowledge from the expert consisted of soliciting the expert's reactions to the formalized and implemented test cases with a demonstration of the expert system. The expert's feedback was valuable in several ways, the most important of which was to validate the correctness of the work done by the knowledge engineers in transferring knowledge from the expert to the program. During the demonstration, the knowledge engineers and the expert verified that the program was emulating the expert's problem-solving techniques. The demonstration also provided a forum for reviewing the clarity and ease of use of the demonstration system's interface.

First Cycle of Knowledge Acquisition

The knowledge transfer process began with a seminar presented to the ES2 Engineers. It included an introduction to expert systems and the knowledge acquisition process along with a demonstration of an experimental rule-based system that was written in INSIGHT (PC-based software) for diagnosing problems in a trickling filter. The ES2 Engineers recommended starting with the primary sedimentation (clarifying) tank because it would have an appropriate level of complexity.

The first test case was developed during an informal interview while a knowledge engineer tape-recorded the conversation. The expert took an active role in the knowledge acquisition exercise by acting as if he were teaching the knowledge engineers how to solve the test case.

Using the information from this interview, the knowledge engineers implemented the first version of Sludgecadet, the proof-of-concept system discussed in the next section. To validate the implemented knowledge, the Sludgecadet system was demonstrated to experts for their review. All participants watched the expert system work and were given the opportunity to use it themselves. Their comments were detailed and emphasized the choice of specific words and phrases used in the system. Since they found the underlying reasoning and facts to be represented correctly, their comments emphasized the need to make Sludgecadet understandable and accessible to the novice WWTP operator.

On an earlier site visit, the knowledge engineers had obtained a copy of the Fort Lewis O&M manual. Using this information, the knowledge engineers prepared a version of Sludgecadet that transferred the general solution of the total suspended solids problem to the Fort Lewis plant. This version of Sludgecadet contained all facts and knowledge from the Fort Lewis plant that applied to the test case. The experts reviewed this version, focusing on its details and determining its applicability to the Fort Lewis WWTP.

Technical Feasibility of the Sludgecadet System

The purpose of the Sludgecadet proof-of-concept system was to apply the process of building an expert system to a representative diagnostic problem. With help from the participating experts, the team focused on diagnosing and recommending remedial action for a specific operating problem: abnormally high total suspended solids (TSS) in the primary clarifier effluent. The first version of Sludgecadet consisted of facts, calculations,

and diagnostic and remedial expertise that is transferable to individual sites in the category of WWTPs with trickling filters for secondary treatment and anaerobic digesters for sludge treatment. In addition, this test version had complete user interface and explanation facilities that had been reviewed by experts and potential users at ES2 Engineering and Fort Lewis.

Before implementing the Sludgecadet system, the following tasks were necessary:

1. Compile a description of the domain knowledge
2. Formalize the information resulting from the knowledge acquisition exercise
3. Review applicable AI programming techniques
4. Choose appropriate software.

To support the technical feasibility of the Sludgecadet proof-of-concept system, the results of each task are described below.

Description of the Domain Knowledge

During the knowledge acquisition process, knowledge was compiled primarily from experts, but also from operating manuals, engineering texts, and plant engineering descriptions. Since the focus was on developing an expert system for one specific type of operating problem, the team concentrated on gathering only those facts and problem-solving techniques applicable to that problem. From the various sources, it was established that the acquired knowledge could be separated into three categories: facts about the treatment plant and operating data; reasoning for making diagnoses and recommending solutions; and calculations for the various empirical and dimensional relationships in a WWTP.

In addition to categorizing the knowledge, there are some interesting characteristics in the domain of diagnosing and recommending remedial action in WWTPs. These include the types of decisions embedded in diagnosing and recommending remedial actions, the data requirements for these decisions, and the operator's level of expertise.

Cortinovis has presented a conceptual framework to describe operating decisions in four categories:[14]

- Planning Decisions: preparing for new or expanded facilities, formulating staffing plans, and preparing budgets
- Administrative Decisions: dealing with personnel, boards, regulatory agencies, and the public
- Process Decisions: setting targets for process parameters
- Operating Decisions: making necessary changes on each shift to keep the plant on target for process parameters.

[14] D. Cortinovis, *Controlling Wastewater Treatment Processes* (Ridgeline Press, Lafayette, CA, 1984).

Of these four categories, diagnosing and recommending remedial actions are grouped under "process decisions" and "operating decisions." Each type of decision can be based on heuristics or algorithms. Heuristics include qualitative or symbolic problem-solving rules developed from operating experience. An example of a heuristic rule for diagnosing problems with trickling filter processes is: "If the trickling filter has an obnoxious odor problem, the wastewater, sludge, or biological growths have become anaerobic."[15]

Algorithms include empirical or theoretical models. A solids mass balance calculation is an example of an algorithm that would be used to test process performance. Computers have been useful in helping the operator make such calculations.

During treatment plant operations, the operator must respond to changes in plant status by "taking action." Sometimes taking action means establishing routine activities such as sampling, buying supplies, and scheduling maintenance. At other times, the operator must take action in response to adverse process conditions. Some typical operator actions are:[16]

- Set operations goals and targets for process parameters
- Take physical action, e.g., change flow, add chemicals, repair broken equipment
- Maintain automatic control equipment, e.g., if automatic control equipment is installed, the operator is responsible for setting the automatic control parameters as well as maintaining the equipment
- Determine if additional expertise is required to solve an operational problem.

To run a WWTP, the operating staff must keep track of the present state of the ongoing processes. This status is evaluated by indicators that show influent flow rate, temperature, pH, biological oxygen demand (BOD), settleable solids, SS, color, odor, and process turbulence patterns. Some of the indicators are measured empirically; others are based on the operator's subjective observations. The empirical data are associated with standard units of measurement; the subjective data have no standard of measurement. Methods of collecting information about these indicators include personal observations, manual sample collection and laboratory analysis, and automatic data collection.

One of the operator's essential duties is to walk through the plant and observe its present state. Familiarity with the plant, coupled with personal observations, are essential to being an effective operator. Also, plant processes are dynamic; the operator must understand the impact of changes on the plant. Since each plant is unique, operator training is most effective with hands-on, site-specific conditions.

Laboratory results and measured parameters are necessary to operation and serve to enhance, rather than replace, direct operator observations. Laboratory analysis is an empirical method for collecting data about the status of a plant. Aside from being required by Federal, State, and local regulatory agencies, such analysis is also vital to the operator for monitoring and interpreting plant conditions. Without laboratory results, the operator can only guess at what is happening in the plant.[17]

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[15] D. Cortinovis, et al., *The Activated Sludge Process: Fundamentals of Operation* (Ann Arbor Science, 1983).
[16] D. Cortinovis; D. Cortinovis, et al.
[17] D. Cortinovis.

Formal Representation in Sludgecadet

The first step in testing the system's feasibility is to rewrite the acquired knowledge into a formal documented form that is independent of a specific type of expert system or programming environment. There are several reasons for this step. First, it forces knowledge engineers to restate the acquired knowledge, thus checking their understanding of the domain. It also provides a medium for validation and review by the contributing experts. Finally, since the knowledge is already recorded in a formal, validated medium independent of implementation language, it allows efficiency in rewriting the same system in a different language.

After formalizing the knowledge, the team designed five basic features and capabilities of the Sludgecadet system which include:

1. Storage of and access to facts about the plant. Two important constraints guide the formalization of knowledge: the facts describing the generic and site-specific plant information need to be stored separately, and there needs to be a provision for high-capacity data storage with easy updating and access, such as a database. An interesting feature of wastewater treatment facts is that they concern complex objects with physical meanings and behaviors. For example, pumps are physical objects in wastewater treatment plants. All pumps share certain attributes (e.g., a class, a model number, a pressure rating, etc.); specific pumps have specific values for each of these attributes.

2. Reasoning for making diagnoses and recommending remedial action. The reasoning process that includes diagnosis and recommendation of remedial action has been formalized frequently in the expert system programming environment. These systems have represented the diagnostic process as one that attempts to prove a hypothesis about the problem (i.e., the diagnosis) by searching a database for proven facts or prompting the user for confirmation on certain questions (i.e., new symptoms). This reasoning exercise is usually called a "backward chaining" process because it starts with a posed hypothesis, tests the hypothesis with various supporting facts (i.e., premises) and, if the premises are true, indicates that the hypothesis has become a proven solution. The diagnostic process is represented conveniently by statements called "production rules" in an "if...then...else" format.

3. Engineering calculations. The ability to do calculations is an inherent part of any computer program in the engineering domain, which encompasses wastewater treatment. The need for computations arises in many situations: transforming raw data from samples to reportable results, checking and setting the operational parameters, creating required plant reports, verifying data, and diagnosing problems. Not only do computations need to be performed from within the reasoning process, but the Sludgecadet system also must provide answers to computations at the operator's request.

4. Program control. This feature enables the user to control execution of the expert system; these tasks include inputting data, outputting results, requesting engineering computations, accessing the database, initiating operating problem diagnosis and recommending remedial action, and requesting explanations.

5. User interface and explanation. The user interface provides tools that enable the user to interact with the expert system and exercise control over the program. Unfortunately, this is the single part of the program design that depends on the software and hardware chosen for system implementation. Classically, this interaction has been based on text input and output. With a text-based interface, the terminal can be either a teletype (typewriter) or a screen on which the lines are written in consecutive order from

top to bottom. With both graphics monitors and software, personal computers and workstations can provide an interface based on menus, pictures and, in some cases, a mouse-guided cursor. Most importantly, graphics provide the entire screen to the user for both input and output. A typical graphics interface consists of pictures (i.e., bitmaps) and menus that are cursor-sensitive. By selecting a picture or menu item with the cursor, the user activates a part of the software. Cursor-sensitive graphics can be used as an interface to program control and for inputting and displaying data.

Another aspect of the expert system's interface is a feature that explains the system reasoning, conclusions, and requests for information. The explanation facilities can reply to questions that are posed such as, why the user is asking for this piece of data or how the user forms that diagnosis. The specific design of the explanation facilities depends as much on the capabilities of the expert system's interface as it does on the users' needs and level of expertise. For this reason, it is to the advantage of the system designer to be able to work in a programming environment that provides as many built-in features as possible for responding to the system's potential users.

AI Programming Techniques

AI offers many alternative methods for implementing the representation required by the Sludgecadet system. Of these, two particularly promising AI programming techniques for the Army WWTP O&M are the object-oriented and failure-driven learning methods. Although the former was used in this exercise, the latter has some advantages. For example, a failure-driven system would have lower peripheral storage and software development costs. Specifically, the parent frames would contain most of the decision functions. However, disadvantages are the time required for software evolution through the plant failure detection/correction and the level of operator skill required during the training phase.

Nilsson has stated that the appropriateness of the representation depends on the application; further, efficient storage, retrieval, and modification are key concerns in selecting an implementation design.[18] Considering the enormous amount of information on O&M of WWTPs, the developmental team chose an object-oriented programming style as the guiding framework for designing the implementation.

Object-oriented programming focuses on the use of formal data structures as the heart of the implementation code. In its logical extent, object-oriented programming refers to all code units such as variables or functions (i.e., subroutines) as objects. "Objects" usually refer to items in the real world that have physical meaning. A useful application of object-oriented programs is as an interface to information in a database. For example, rather than pull information from a database into a program's variables and then process it, object-oriented programming provides a paradigm for referring to and processing the information directly in the database. The most advantageous way to use this style of programming is with system development tools that provide a procedural and production rule system using an object-oriented style and capabilities for database information processing.

One AI programming technique for organizing information about a specific object is a type of data structure called "frames." Frames are data structures identified by a unique name and consist of a set of attributes and attribute values describing the

[18] N. Nilsson, p 361.

object.[19] Frames often are organized into a hierarchical database, with some frames representing general level "class" objects and others detailed level "instance" objects. Class-level frames can be considered as parent objects that pass on their attributes to instance or child frames. When a new child frame is created, it will automatically inherit the attributes of the parent unit, thus establishing an efficient method for generating and organizing information in the database.

Expert systems comprise a branch of AI programming designed to accommodate the following features: expert-level solutions to complex problems, solutions that are understandable to the user, and a flexible design that accepts new knowledge.[20] As was shown in Figure 1 and discussed earlier, the two main parts of an expert system are the knowledge base and the inference engine. Depending on the expert system programming tool being used, inference engines include different types of controlling strategies for scanning the facts and ordering the rule-testing sequence. Two examples of inference control strategies are forward-chaining and backward-chaining. A forward-chaining strategy is considered to be data-driven because it triggers with the assertion of facts that form rule premises. Backward-chaining is called a "goal-directed" strategy because it tests the validity of a specific rule conclusion by searching the knowledge base for valid facts in associated rule premises. Expert systems with this design often are called "production systems," and the encoded rules are called "production rules."

"Daemons" are rule-based or procedural items of code that execute when a certain attribute's value changes. A daemon is attached to an attribute and constantly monitors the condition of the attribute value. When the value changes, the daemon executes. Daemons are so called because they do not require explicit control by the user, but are often activated as "side effects" when some other procedure changes an attribute's value.

It was clear that the object-oriented style database would be advantageous for Sludgecadet, producing a system with a procedural language for program control and calculations as well as a database for storing the plant and operating data. Other desirable features included object-oriented production rules with flexible inference mechanisms, including forward and backward chaining; high-level control of text; and graphics interface and explanation facilities.

Choosing Implementation Software

The workstation (e.g., LISP machine or general-purpose unit) environment was chosen over the PC because the specific needs of the application should dictate software selection.

The Sludgecadet system was tested and then implemented in a Knowledge Engineering Environment (KEE) that resides in a LISP-based workstation. Of its many features, those most applicable to the proof-of-concept version of Sludgecadet are: frames that form a database of objects connected by attribute inheritance relationships; procedural programming language (LISP), accessed either by message passing between objects or as explicitly invoked functions; built-in explanation facilities; and a machine-independent, high-level graphics package for building a customized user interface.

At the center of KEE are frame-based objects called "units." Frames are collected into a knowledge base (KB). They can exist independently in a KB or can be linked by

[19] N. Nilsson; B. Buchanan and E. Shortliffe.
[20] B. Buchanan and E. Shortliffe.

relationships. Specifically, KEE provides "child of" or "parent of" links. With these links, the child frames can inherit attributes of their parent frames. Parent frames describe classes of objects.

KEE has another feature called "active values," sometimes known as daemons. This feature can be invaluable for maintaining and updating dependent values in the plant and operating database. In KEE, daemons are stored as method attributes on a special kind of unit that is a child of the class "active values."

KEE also provides a practical delivery or run-time environment called "PC-Host." The premise of the delivery environment is that the system developer designs and implements the expert system on a LISP workstation, then shifts (i.e., "ports") the expert system code to a VAX (e.g., that operates under VMS). By residing on a VAX, the expert system can be accessed by users with IBM-compatible PCs through a telephone or network communication line. The IBM PC must have certain features: at least 512K memory, a graphics card and monitor, and some form of communication capability. However, the required configurations are fairly standard and most PCs already have graphics and communications features.

Implementation of Sludgecadet

The representation described above was tested by implementing the Sludgecadet prototype for the problem of abnormally high TSS in the primary clarifier effluent. The Sludgecadet expert system can:

- Recognize that an operating problem involves the primary clarifier and offer a possible diagnosis
- Diagnose a problem or, if unable to infer a diagnosis, state that diagnosis is unknown
- Represent the physical objects of a wastewater treatment plant (e.g., unit processes, subsystems, specific parts, wastewater and sludge streams)
- Provide a graphics-oriented interface that emphasizes use of menus and a mouse.

This exercise was implemented with the same AI programming techniques that would be used in a production version of the Sludgecadet system. The current version of Sludgecadet consists of two KEE KBs: the first named SLUDGECADET for knowledge that is transferable between locations and the second named FORTLEWIS for the chosen test site. These KBs contain all codes that implement the facts, production rules, and most of the interface within frames (or KEE units). The only code not stored in the two KBs is the LISP code required for procedural control of the program.

The SLUDGECADET KB can be displayed graphically (Figure 2) as a "KB graph" with inheritance of attributes shown explicitly by connecting lines between the units. In the KB graph, each unit is represented by name; to the left are the parent units and to the right are the children units. In other words, attributes are passed from left to right (from parents to children); the more general units (class-level) are distinguished by being on the left end of a connecting line; the more specific units (those representing instances where

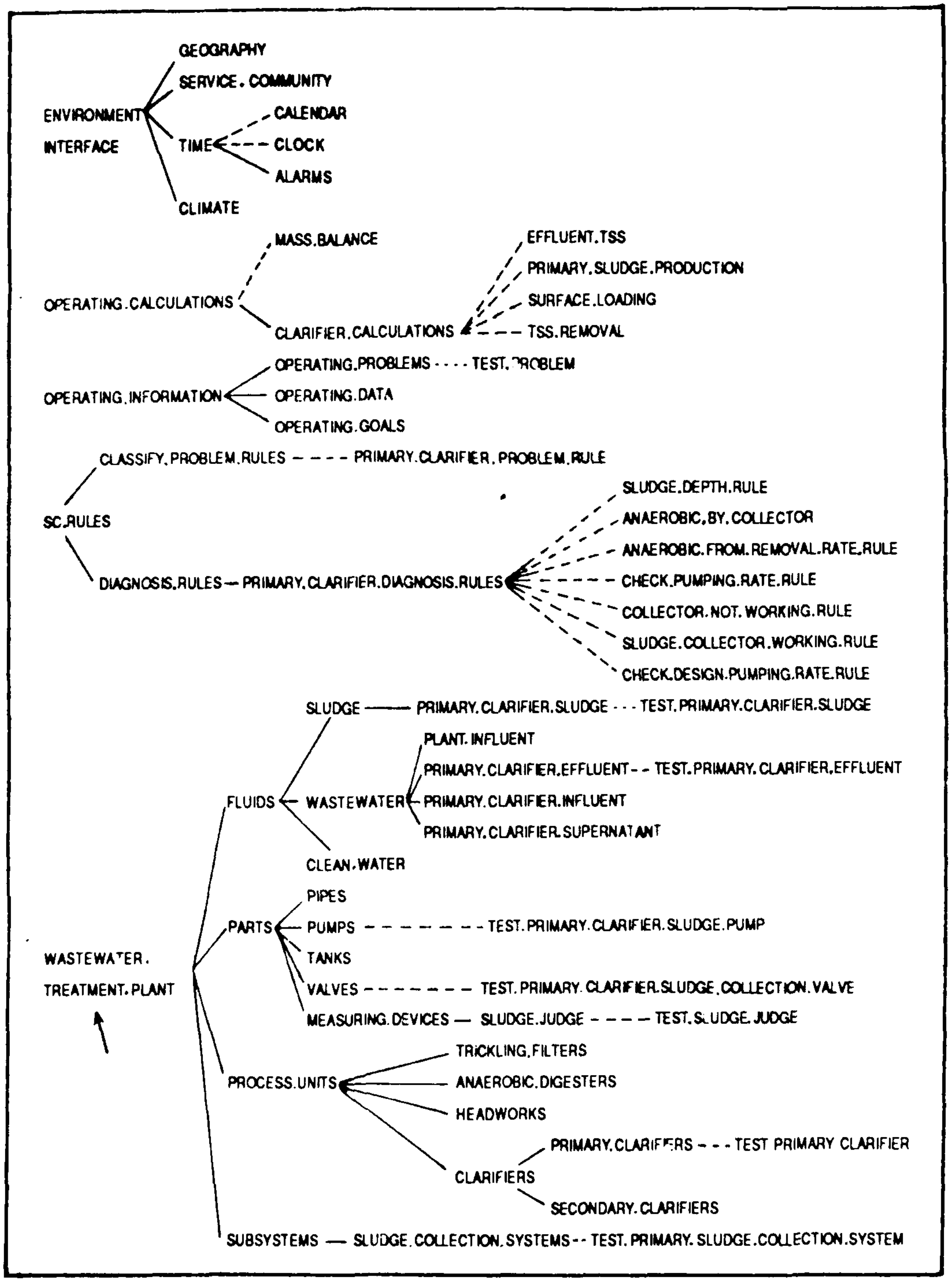

Figure 2. Graph of the Sludgecadet knowledge base.

of physical objects) are on the right end of a dashed line. The frame representation in the SLUDGECADET KB includes:

1. Environment. The frame ENVIRONMENT serves as an organizational frame for other class frames that describe characteristics of the geography, service community, time, and climate.

2. Operating calculations. This is the parent frame for all calculations required in the TSS problem. All information needed for a specific type of calculation is stored in each instance frame's attributes.

3. SC (Sludgecadet) rules. In KEE, each production rule is stored as a special type of frame instance. Each rule is stored in the instance frames at the right of the SC RULES hierarchy. Sludgecadet has two classes of rules: one for a preliminary analysis of a new problem called CLASSIFY PROBLEMS RULES AND DIAGNOSIS RULES. For this problem, a specific class of rules called PRIMARY DIAGNOSIS RULES was created.

4. Operating information. In the Sludgecadet design, each operating problem is described by a specific frame in order to record a history of operating problems. That class frame, OPERATING PROBLEMS, is the parent unit for each problem frame.

5. Plant description. The object WASTEWATER TREATMENT PLANT collects the class-level objects: FLUIDS, PARTS, PROCESS UNITS, and SUBSYSTEMS. FLUIDS is the parent unit for the classes SLUDGE, WASTEWATER, and CLEAN WATER, which in turn are parents of the various types of fluids found in WWTPs. The object instance TEST PRIMARY CLARIFIER SLUDGE was used to test the rule and was replaced by Fort Lewis object instances. The PARTS object is the parent frame for specific categories of plant parts. The various unit process frames fall under the PROCESS UNITS class. The SUBSYSTEMS unit represents plant parts usually designated as a group (e.g., the sludge collection system).

The FORTLEWIS KB (Figure 3) was created by running an installation procedure on the SLUDGECADET KB that creates all requisite frames and queries the user for all values that describe a specific WWTP. The attributes for the FORTLEWIS KB frames do not have to be completely recreated because they are all inherited from the associated parent frame in the SLUDGECADET KB.

The attributes (called "own slots" in KEE) inherited by the unit PRIMARY CLARIFIER 1 (Figure 4) include: ACTUAL SLUDGE PUMPING RATE, DESIGN SLUDGE PUMPING RATE, DOWNSTREAM, EFFLUENT, EFFLUENT SS, FRACTION DRY SOLIDS IN SLUDGE, and GAS BUBBLES. Each slot has several subdivisions called "facets" such as Inheritance, ValueClass, Cardinality Max, Comment, and Values. The Inheritance facet specifies the way in which the slot inherits the value facet from a parent unit; in the slot ACTUAL SLUDGE PUMPING RATE (top slot of Figure 4) the inheritance of override values means that the value, in this case 15, is unique to the unit PRIMARY CLARIFIER 1 and has not been inherited from the PRIMARY CLARIFIERS parent unit. The ValueClass facet declares that the value of the slot must belong to a certain category which in this slot is a number. A Cardinality Max establishes the upper limit of the number of distinct values on the Values facet. A Cardinality Max of "1" means that the slot can have only one value at a time. The values in the rest of the slot of PRIMARY CLARIFIER 1 reflect the current state of the KB after diagnosing the TSS problem.

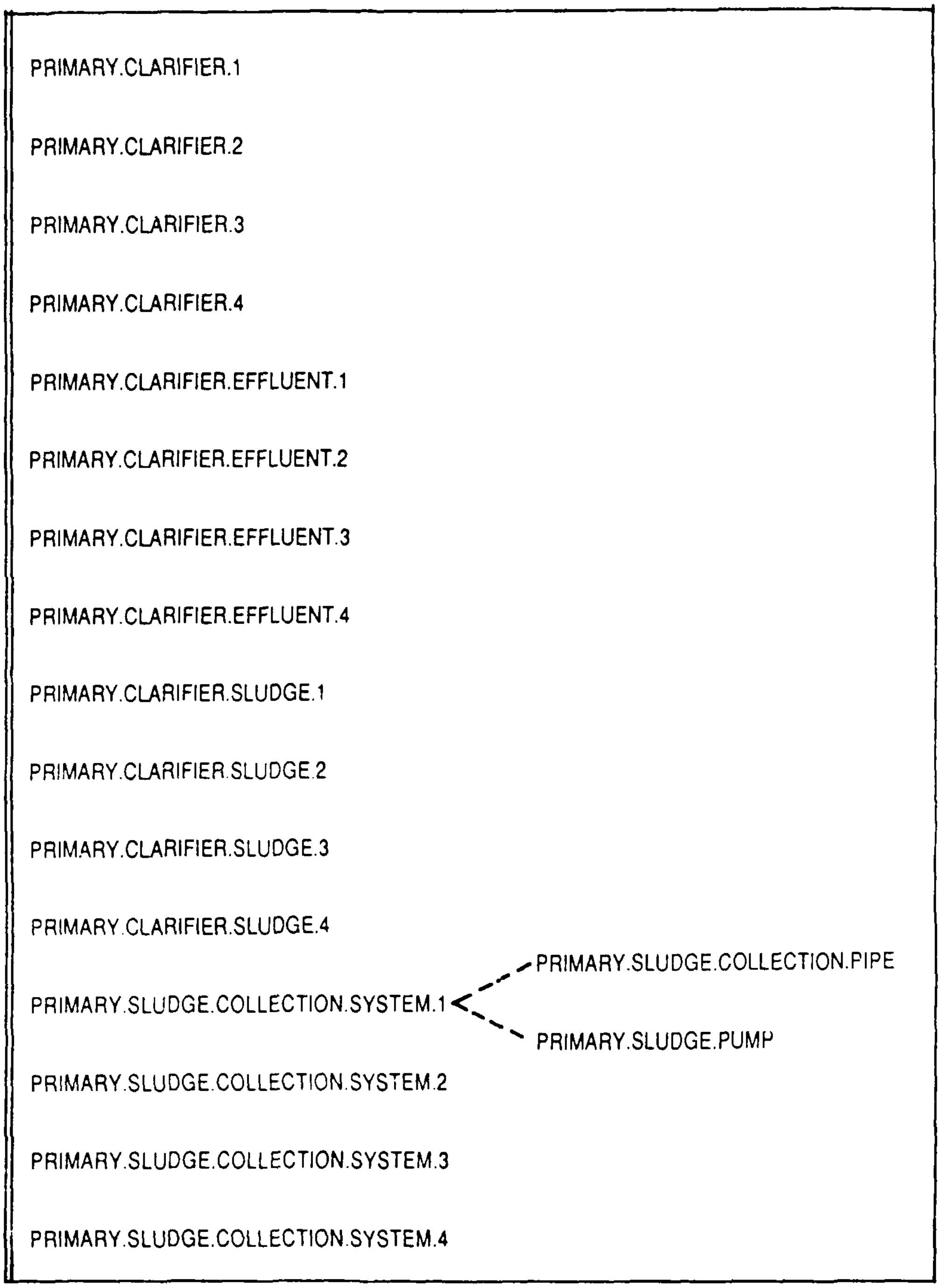

Figure 3. Graph of the FORTLEWIS knowledge base.

```
Unit: PRIMARY.CLARIFIER.1 in knowledge base
FORTLEWIS
Created by PERMAN on 5-Mar-87 22:13:09
Modified by PERMAN on 8-Mar-87 21:24:18
 Member Of: (PRIMARY.CLARIFIERS in kb SLUDGECADET)

Own slot: ACTUAL.SLUDGE.PUMPING.RATE from
PRIMARY.CLARIFIER.1
 Inheritance: OVERRIDE.VALUES
 ValueClass : ( NUMBER in kb KEEDATATYPES)
 Cardinality.Max: 1
 Values: 15

Own slot: DESIGN.SLUDGE.PUMPING.RATE from
PRIMARY.CLARIFIER.1
 Inheritance: OVERRIDE.VALUES
 ValueClass: (NUMBER in kb KEEDATATYPES)
 Cardinality.Max: 1
 Values: 22

Own slot : DOWNSTREAM from PROCESS.UNITS
 Inheritance: OVERRIDE.VALUES
 Comment: "A pointer to the unit process unit that is
downstream."
 Values: Unknown

Own Slot: EFFLUENT from PRIMARY.CLARIFIER.1
 Inheritance: OVERRIDE.VALUES
 Comment: "Pointer to the appropriate effluent unit."
 Cardinality.Min: 1
 Cardinality.Max: 1
 Values: PRIMARY.CLARIFIER.EFFLUENT.1

Own slot: EFFLUENT.SS from CLARIFIERS
 Inheritance: OVERRIDE.VALUES
 ValueClass: (NUMBER in kb KEEDATATYPES)
 Cardinality.Min: 1
 Cardinality.Max: 1
 Comment: "Effluent suspended solids (mg/l)."
 Values: Unknown

Own slot: FRACTION.DRY.SOLIDS.IN.SLUDGE from
CLARIFIERS
 Inheritance: OVERRIDE.VALUES
 ValueClass: (NUMBER in kb KEEDATATYPES)
 Cardinality.Min: 1
 Cardinality.Max: 1
 Values: Unknown

Own Slot: GAS.BUBBLES from PRIMARY.CLARIFIER.1
 Inheritance: OVERRIDE.VALUES
 Values: VISIBLE
```

Figure 4. The PRIMARY CLARIFIER 1 frame and attributes.

One of the rules used in diagnosing the TDS problem is called the "Primary Clarifier Problem Rule" and is stored in a frame of the same name (Figure 5). All of a rule frame's attributes are inherited from the high-level KEE frame called RULES. A system developer enters a rule into a KB by storing it in the value facet of the EXTERNAL FORM slot of a rule frame (see the fourth slot in Figure 5). The rule text is in a LISP-like form with each premise enclosed by parentheses. Most premises have the format "the slot of frame is value," thus associating each rule premise to frame-based information in the KB. The "?Problem" and "?Unit.process.location" terms, which are distinguished from other terms by a question mark, are KEE rule variables. By using the ?Problem variable, this rule can be applied to any problem represented by a frame which is a child of the class frame OPERATING PROBLEMS. This action is controlled by the premise "(?Problem is in class operating problems)."

Program Control

The Sludgecadet program control triggers several capabilities: (1) installing the program at specific WWTPs, (2) inputting operating and plant data, (3) reporting data and program results, and (4) diagnosing operating problems and recommending remedial action. The program control is implemented with LISP and is activated with KEE active-image Method Actuators.

Problem-Solving by Reasoning

Diagnosing problems in WWTPs is much more complex than simply diagnosing a particular solution to a specific operating problem. An experienced operator can review problems experienced in the past and try to solve a new problem by looking for similarities or associations with past difficulties. For optimal effectiveness, an experienced operator should first see if a problem is really an operating problem or if it is due to some other factor.[21] One of the first steps in problem diagnosis is to relate similarities about the current problem to those in the past and ascertain if the current problem may be caused by something over which the operator has no control.

Reasoning is implemented in the preliminary analysis phase of diagnosing a problem in the Sludgecadet system. In the current version, preliminary analysis consists of a rule (e.g., the Primary Clarifier Problem Rule) with a forward-chaining strategy that asserts a hypothetical diagnosis if the problem is related to operation of the primary clarifier and a procedure (written in LISP) that creates a frame for a new problem. A problem frame's attributes include the date the problem was noticed, a diagnosis if one was made, action taken to remedy the problem, and the location of the problem. This configuration allowed successful testing of the feasibility for creating a database of problems and for identifying operating problems.

The second phase of diagnosis uses the problem's hypothetical solution from the preliminary analysis as a goal in a backward-chaining inference exercise. Since this exercise makes use of more than one rule, the inference engine "chains" the rule by matching similar conclusions from one rule to the premises of another rule to form a rule graph. As the program chains from the goal to each supporting fact, the Sludgecadet system first checks if the fact is available in the KB; if not, then the user is queried. If a diagnosis is made, the results, which are displayed by Active Images, include the diagnosis of the problem, the primary cause or reason for the problem, and the recommended remedial action.

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[21] U.S. Environmental Protection Agency (USEPA), *Handbook: Improving POTW Performance Using the Composite Correction Program Approach*, EPA 625/6-84-008 (October 1984).

```
Unit PRIMARY.CLARIFIER.PROBLEM.RULE in knowledge base
SLUDGECADET
Created by PERMAN on 3-Dec-86 22:46:49
Modified by PERMAN on 7-Dec-86 19:34:49
 Member Of CLASSIFY.PROBLEM.RULES

 Rule takes primary symptoms, asserts a problem unit and queries for a
diagnosis.
```

```
Own slot: ACTION from RULES
 Inheritance UNION
 Values: Unknown

Own slot: ASSERT.MODE from CLASSIFY.PROBLEM.RULES
 Inheritance: OVERRIDE.VALUES
 ValueClass (ONE.OF ADD REPLACE)
 Cardinality.Min: 1
 Cardinality.Max: 1
 Values REPLACE

Own slot ASSERTION from PRIMARY.CLARIFIER.PROBLEM.RULE
 Inheritance UNION
 Avunits: (WFFINDEX in kb RULESYSTEM2)
 Values #Wff (A PROBABLE CAUSE OF ?PROBLEM IS THE SLUDGE.
IS ANAEROBIC)
```

```
Own slot EXTERNAL.FORM from PRIMARY.CLARIFIER.PROBLEM.RULE
    Inheritance SAME
    ValueClass (LIST in kb KEEDATATYPES)
    Avunits (RULEPARSE in kb RULESYSTEM2)
    Values: (IF
            (AND (?PROBLEM IS IN CLASS OPERATING.PROBLEMS)
             (THE UNIT.PROCESS.LOCATION OF ?PROBLEM IS
              ?UNIT.PROCESS.LOCATION)
             (?UNIT.PROCESS.LOCATION IS IN CLASS
              PRIMARY.CLARIFIERS)
             (THE TOTAL.SUSPENDED.SOLIDS OF
              ?UNIT.PROCESS.LOCATION IS TOO HIGH)
             (THE GAS.BUBBLES OF ?UNIT.PROCESS.LOCATION IS
              VISIBLE)) THEN
           (THE PROBABLE.CAUSE OF ?PROBLEM IS
            THE.SLUDGE.IS.ANAEROBIC))
Own slot: PARSE from RULES
 Inheritance METHOD
 ValueClass: (METHOD in kb KEEDATATYPES)
 Values DEFAULT.RULE.PARSER
Own slot PREMISE from PRIMARY.CLARIFIER.PROBLEM.RULE
 Inheritance UNION
 Avunits (WFFINDEX in kb RULESYSTEM2)
 Values #Wff (?PROBLEM IS IN CLASS OPERATING.PROBLEMS)
        #Wff (A UNIT.PROCESS.LOCATION OF ?PROBLEM IS ?UNIT.
PROCESS.LOCATION) Wff (?UNIT.PROCESS.LOCATION IS IN CLASS PRIMARY.
CLARIFIERS)
        #Wff (A TOTAL.SUSPENDED.SOLIDS OF ?UNIT.PROCESS.
LOCATION IS TOO HIGH)
        #Wff (A GAS.BUBBLES OF ?UNIT.PROCESS.LOCATION IS
VISIBLE)
```

Figure 5. The Primary Clarifier Problem Rule frame and attributes.

User-Oriented Interface and Delivery Feasibility

The Sludgecadet interface was designed to be simple to use and as self-explanatory as possible to facilitate use by a novice operator. The developers took full advantage of the graphics features of KEE by using cursor-activated menus and data input windows whenever possible. One of the goals of this kind of interface is to minimize the amount of time the operator would have to spend typing in data and commands.

The interface as seen by the user, not the developer, consists of two panels: Sludgecadet control and plant/operating information (Figure 6). Program control is activated by using the cursor to select one of the rectangles labeled INITIALIZE, IDENTIFY.A.PROBLEM, or DIAGNOSE.A.PROBLEM. The results of and explanation for the diagnostic process are displayed by the rectangles entitled Solution, Primary Cause, Diagnosis, Probable Cause, and Unit Process Location. The operating data interface provides examples of active images that are used for input as well as output. For example, the rectangle entitled "Actual sludge pumping rate" contains a number that can be changed by superimposing it with the cursor and using the up-arrow key to increase it or the down-arrow key to decrease it.

A Development Strategy for Sludgecadet Enhancements

A logical strategy for extending the Sludgecadet system is to add knowledge for operating problems other than the TSS exercise discussed above. An ideal production version of Sludgecadet would be able to diagnose all possible problems for the category of WWTPs with trickling filters for secondary treatment and with anaerobic digesters for sludge treatment. The next stage in developing Sludgecadet would focus on identifying *representative* operating problems to accommodate typical, but not necessarily complete, examples of what might actually occur. Although specific problem examples were not identified for this study, the following categories of problems would be considered:

- Biological processes
- Physicochemical processes
- Interaction of one failure with others in the plant
- Abnormal data trends
- Environmental or external problems.

Program expansion to the following areas is conceivable:

- Operators' training
- Minimization of energy and chemical costs
- Plant operation and laboratory records management
- Compliance in reporting requirements
- Preventive and scheduled maintenance
- Planning, scheduling, and budgeting.

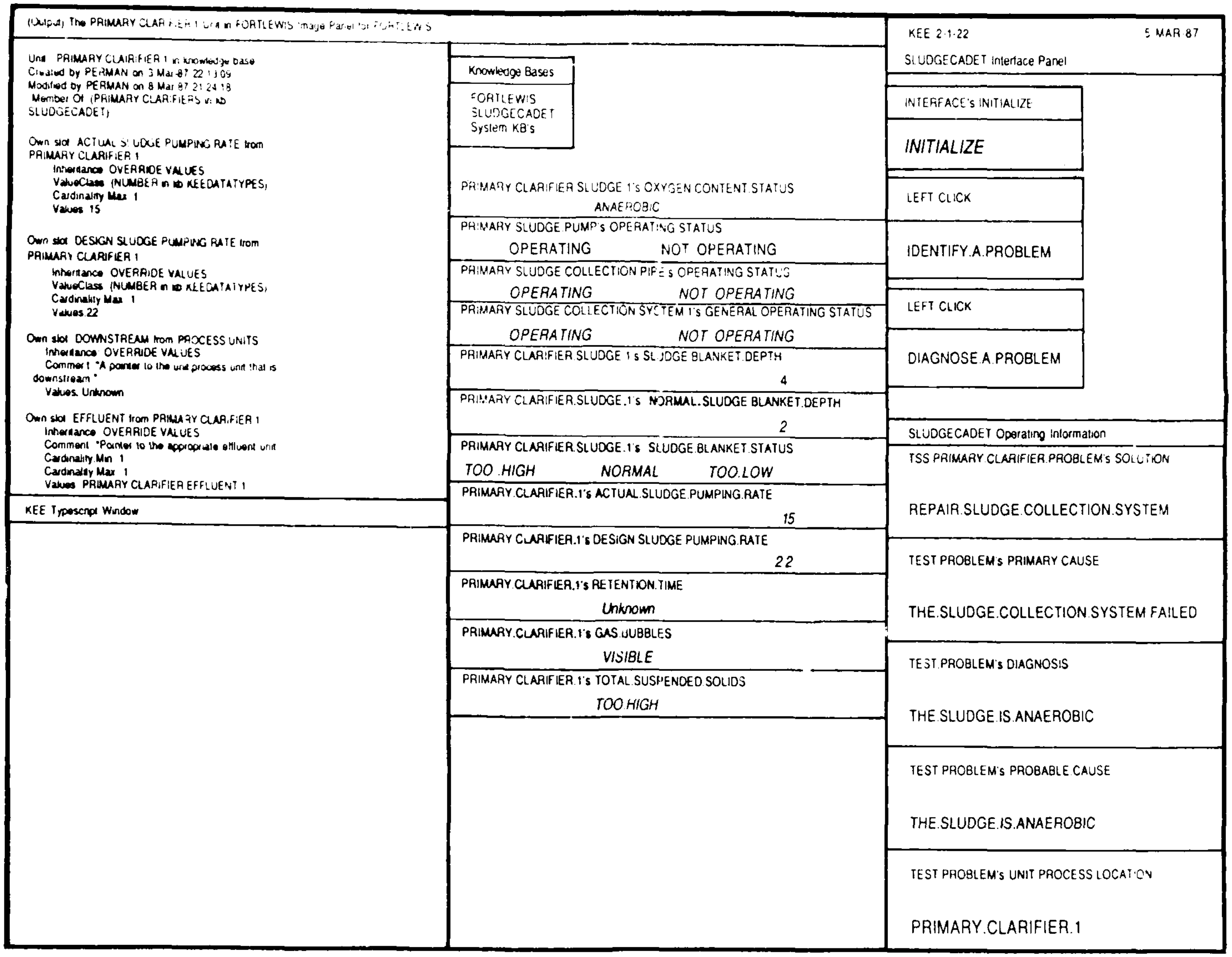

Figure 6. The Sludgecadet interface.

4 THE PROOF-OF-CONCEPT SYSTEM: DISCUSSION

Like any other software, the pilot Sludgecadet system should be evaluated in terms of both long- and near-term benefits and costs. Benefits would materialize in improved WWTP performance and increased productivity for the system's user. Costs would accrue with system development, software/hardware purchases and maintenance, and user training. Unlike other software, expert system development has additional benefits and costs associated with acquiring and encoding expertise. These include the costs for identification of domain experts, formalization of an expert's problem-solving knowledge, and design of the expert system's explanation facilities. This chapter assesses the advantages and disadvantages to the Army associated with developing and using a WWTP O&M system like Sludgecadet in terms of long-range impacts, near-term impacts of this work, and any immediate extensions.

Long-Term Impacts

Improved Plant Performance

The Sludgecadet system was intended to improve the performance of WWTPs by giving plant operators access to an innovative problem-solving tool and by contributing to their productivity. The most immediate benefit of Sludgecadet would come from assistance in diagnosing plant operating problems and recommending remedial actions. The system would make the problem-solving knowledge of the source experts available to the novice operator. In addition, the system would provide a database for storing and quickly assessing plant and operating information. Sludgecadet was not intended to replace an operator, rather, it provides operating expertise that is not available in standard manuals and combines that knowledge with database and computational facilities to assist operators.

Operator Training

A principle feature of expert system architecture is separation of the KB (i.e., facts, rules, procedures) from the system's control mechanism or "inference engine." By separating the knowledge from control, the components of the KB become accessible for explanation of reasoning and for user tutoring. GUIDON is one example of a commercial expert system designed expressly for detailed explanation and user training.[22] The GUIDON expert system is founded on MYCIN, an expert system that diagnoses microbial blood infections and recommends treatment. GUIDON combines the expertise contained in MYCIN with technology from areas of intelligent computer-aided instruction, such as dialog structuring, generating teaching material, constructing and verifying a model of the student's knowledge, and explaining expert reasoning. During tutorial sessions, the user interacts with GUIDON in case study dialogs in which GUIDON has access to the correct problem solution. GUIDON's purpose is to broaden the student's knowledge by pointing out inappropriate lines of reasoning and suggesting approaches that the student did not consider.

In the longterm, the Sludgecadet system could be used as a foundation for a tutorial system similar to GUIDON. The diagnostic rules, facts, and procedures specific to the domain of WWTP operations would be augmented with the appropriate intelligent

[22] B. Buchanan and E. Shortliffe.

computer-aided instruction technology. It is important to remember that systems like Sludgecadet are only computer programs and are not meant to replace an operator certification and training program.

Costs Associated With System Development and Deployment

Long-term costs associated with developing and deploying a system like Sludgecadet would involve activities for system enhancement, system maintenance, and user support. These costs are incurred as soon as a system is placed in the field and made available to users.

To effectively promote a new software package, it is necessary to educate potential users about the capabilities and benefits of the system. Users will require formal training through short courses, tutorial videos, and/or manuals. In addition, at least one person should be available to answer questions about the system's operation and provide general user support.

The expansion of Sludgecadet into a software package for training would involve separate long-term costs. These costs primarily relate to software development to produce intelligent computer-aided technology. An intelligent training system would not require new hardware or domain-specific software.

A continuing long-term cost would come from personnel requirements for software maintenance. All software systems eventually require maintenance. In-house personnel would have to be trained in the technology required for program maintenance or contractors would have to be used.

Another issue related to maintenance is that of system enhancements. Even though well designed and implemented expert systems can readily accommodate enhancements, there are still costs associated with evaluating and implementing them. Some enhancements are relatively trivial to add; others require extensive efforts in design and implementation. Experts, users, and software specialists would need to evaluate the recommended enhancements and decide if they are valuable enough to be implemented. Once again, the issue would arise as to whether in-house personnel or contractors should be responsible for this implementation.

A striking characteristic of the current commercial expert systems software is its rapid state of flux in both technical capabilities and purchase price. The major companies in the AI software field produce technical and efficiency enhancements on a regular basis. In addition to significant improvements in software capabilities and reductions in cost, the AI hardware market is expected to see major changes in the next few years. Expert systems development hardware is currently shifting from a specialized LISP workstation development environment, in which each brand of workstation employs its own version of the LISP programming language, to generalized workstations that run a standard form of LISP or C programming language. In addition, the cost of these workstations is expected to decline dramatically as more and more companies introduce them into the market.

An even greater change in the hardware market is expected with technical advances in PC architecture. Over the next few years, PCs can be expected to grow significantly in working memory, processing speed, and graphics capabilities. Along with these changes, it is projected that the more sophisticated development expert systems packages, such as KEE, will become available on relatively expensive PCs.

Benefit/Cost Analysis

It is difficult to evaluate the costs and benefits associated with developing an expert system for Army WWTPs. The problem is twofold in that (1) little work has been done outside the Army in developing expert systems for process control in WWTPs and (2) much of the implementation cost of an expert system would depend on the level of instrumentation at existing treatment facilities. The cost of AI hardware and software for any given facility, once the basic software/hardware configuration has been developed, would be small compared with the cost of plant instrumentation. With the recent advent of low-cost/high-power computing hardware such as VAX workstations, the hardware cost for implementation is trivial compared with the annual O&M costs. A workstation with 10 Mb of fast memory and 1 Gb of hard disk can be purchased for less than $20K. An average manyear costs approximately $30K. For an expert system with workstations, it may cost the Army between $100K and $200K to obtain an Armywide license from the manufacturer. This, too, is a rather small investment if distributed over 100 or more treatment facilities Army-wide. The major unknown is the cost required to develop an expert system software tailored for Army WWTP O&M. Since this kind of software has never been developed, cost data for full-scale and even pilot-scale applications is not available. To help determine this cost, the major treatment trains should be identified for in-depth investigation. The cost of installing sensing devices to measure operational parameters and automatic control systems to actuate the plant equipment should be considered.

When data has been collected and reasonable cost estimates made for implementing an AI system for O&M at Army WWTPs, the savings associated with the implementation (in terms of reduced requirements for manpower, energy, chemicals, etc.), could be compared with the cost of implementing the appropriate control systems and the expert system development. It is anticipated that many of these numbers would fluctuate during development due to new innovations in process control systems, microcontrollers for unit operations, and advances in computer hardware and software techniques, all of which would impact the benefit/cost relationship.

Near-Term Impacts

Modular and Iterative Development Approach

Since the proposed system would be developed in an iterative fashion using a modular structure, the current version would always be functional and executable. This developmental approach would make the Sludgecadet program easy to expand and modify. Having a functional version available at all times would permit the program to be tested after each new module is added. An iterative, modular developmental approach would match the requirements of the knowledge acquisition cycle described.

Requirement for Continued Software Development

To continue developing the Sludgecadet system past the initial or proof-of-concept stage, resources for the experts and knowledge engineers would be needed. However, funds for such activities are scarce. Due to a long payback period in comparison to other Operations and Maintenance, Army (OMA) projects, this type of funding is given low priority. As the costs for such systems decline, these systems may become more economically attractive.

Hardware and Software Requirements

The Sludgecadet system could be implemented using any commercially available expert system development tool with the following features: production rules, procedural programming, database, and facilities for creating a user-friendly interface. Commercial expert system development tools fall into two broad categories: those for PCs (e.g., IBM PC or compatible) and those for LISP machines (e.g., all Symbolics LISP machines, Xerox D-Machines 1108 and 1186, Texas Instruments Explorers) or general-purpose workstations (e.g., Sun 3/75/110/140/160/260, Vax AI workstations, IBM RT). Both workstations and PCs are intended as single-user machines.

Expert system development tools available for PCs have the advantages of lower purchase prices (around $500 to $10,000) and availability for the PCs at most Army installations. In any case, the PC hardware has a modest purchase price (around $2000 to $12,000). On the negative side, the PC software is quite limited in representing knowledge, providing enough memory for large systems, and implementing a graphic interface. Expert systems development tools (or "environments") available for workstations provide flexible representation facilities and do not limit the size of the developing expert system. A high-level graphics interface allows the program developer to quickly test ideas ("rapid prototyping") and provides high-level graphics for the user interface. Unfortunately, the cost of these systems is much higher (as of late 1987, around $40K to $60K for the software and $20K to $80K for the hardware).

Other Issues

To implement an effective AI system for Army WWTP O&M, the following items, in addition to those in the above discussion, would have to be considered:

1. Sensing devices. Proper monitoring and control of WWTP processes would not be possible without reliable sensing devices. Even modern technology cannot provide sensing devices that are simple and reliable enough to measure the monitoring and control parameters for WWTP operation. Availability and reliability of sensing devices must be evaluated carefully before expert systems can be constructed.

2. Acceptance of AI technology by the WWTP operators. Some operators may have a negative attitude toward expert systems or computer technology in general. Some operators may regard the system as a threat to their job security. For effective implementation of the expert system, these operators would have to be convinced that the expert system is a tool to improve their plant's operation.

3. Simplicity. It is important to make the expert system's operation as simple as possible. Too many unnecessary features will only confuse the operators and reduce the efficiency.

4. Size and number of WWTPs. As the WWTP size increases, the application of AI will be more cost-effective. Although no attempt was made to determine a cutoff limit for economical plant size in this study, this factor must be evaluated to determine if the expert system implementation would be economical. Workstation connection with all Army WWTPs or a group of WWTPs also must be evaluated.

5. Extent of AI application. Before the expert system is designed, the extent that the expert system will be used must be determined. For example, the expert system may be used only for troubleshooting, or for plant operation and record management, etc.

6. WWTP automation. WWTPs can be automated as long as this change will be cost-effective. When a WWTP is being automated, the future potential use of an expert system should be considered.

5 CONCLUSIONS AND RECOMMENDATIONS

This study has explored opportunities for the Army to exploit recent advances in AI technology for improving O&M at its WWTPs. Based on findings from a proof-of-concept exercise performed in this study, AI/ES has potential application to the WWTP industry; however, there are also limitations. WWTP processes involve many parameters that must be controlled and monitored continuously, often within very strict limits. Current sensors and software based on AI are neither developed enough nor economically justifiable for immediate use in Army WWTPs. However, with the rapid growth in AI technical capability and projected lower cost in the future, this situation can be expected to change, possibly over a very short time period.

The state of the art in AI/ES technology has been reviewed to provide a general orientation for Army personnel who may be required to evaluate its value to their installations.

A proof-of-concept system called "Sludgecadet" was designed and tested to show the feasibility of adapting AI technology for O&M support at WWTPs. Although further development of this system would be impractical at this time, the proof-of-concept exercise has established that AI/ES could have a role in future automation of Army WWTPs. It should be noted that Sludgecadet's feasibility tests were limited to a very small segment of the WWTP process.

The expert system may prove to be an innovative tool for enhancing and extending the Army's limited personnel and budgetary resources supporting O&M at WWTPs. However, since cost reduction and improvement of WWTP performance would be the major reasons for using this technology, it does not appear feasible at present. AI/ES development costs for Army WWTP O&M are currently too expensive and the AI/ES technology has not fully demonstrated the potential for handling the complex treatment process. For these reasons, it is recommended that the Army postpone research and development on such systems until the AI/ES technology has evolved further and becomes affordable. In addition, it is recommended that any installations considering purchase of AI/ES-based devices perform a cost-effectiveness study to determine if an alternative technology would be indicated.

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